Energy Consumption Prediction of Residential Sector in Post-Pandemic Conditions Using Artificial Neural Networks

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Abstract: ***The lockdown measures for preventing the spread of COVID-19 ended in most countries in the last year. Even so, a lot of things have changed in the routine of most people and mostly in the politics of many companies. The war in Ukraine and the embargo's set on Russian Federation made the last year extremely unstable not only politically but also on the energy market. The most important qualities of any system are the stability and predictability that allow all players to have clear directions and guidelines. This being said, most predictability methods that are commonly used for establishing energy policies are no longer accurate. The purpose of this paper is to present alternative predictive methods that can take into consideration the new dynamics on the energy and political unstable conditions. Using Artificial Neural Networks can be a solution for quick determination of energy consumption in such dynamic changing environments.***

Keywords: energy consumption, residential sector, artificial neural networks, post-pandemic, public policy**,** energy crisis

1. Introduction

In the last 15 years we showed that we can accurately predict the energy consumption for the residential sector by using artificial neural networks and that using this method is often more reliable than the calculation methods based on normative values of consumption. The standard methods are based on functionality and standard needs and don't take into consideration the dynamic relations between all the variables that come into play and the real energy and resource consumption. The two values can sometimes vary significantly because there are a lot of factors that are not taken into consideration (the human factor for ex.) just because there are no standards for them, we don't know the impact that they have (the rate of unemployment for ex.) or we don't have a linear mathematical relation between them and the final energy consumption value.

In the last two years this gap between the prediction of energy consumption and the statistical values became even larger because of the unforeseen changes in the policies of different countries, the energy crisis, the post-pandemic behavior and of course because of the war in Ukraine.

Using artificial neural networks to predict energy consumption in the residential area allows us to use the latest data and statistics in real time and to adjust the networks by adding new variables that come into play and by adding new data to the training set.

In the past published work we built, trained and released different ANN's that could accurately predict energy consumption for different households and urban environments and as long as the parameters stayed between certain limits, the predictions were acceptable.

Running the predictions for the year 2022 and comparing the data with the statistics we can see that the energy consumption in the residential sector starts to differ from the prediction significatively.

In order for the prediction to be accurate we need to update the neural network to take into account the new behaviors of the population.

In order to understand the new energy consumption behavior, we have to look at the global changes in energy policies and the global events that shape them, to understand the effect on the general population and to gather as much data as possible to further train the neural networks.

The main goal is to have a reliable method of prediction that is updated and always ready to use in order to determine what would be the effect of an energy consumption increase or decrease. Having such an effective tool would allow people to prepare for the future energy crises, to establish accurate energy policies and to plan the transition from fossil fuels to regenerative sources without short-comings.

The artificial neural network can learn non-linear relations between the parameters and they can determine what kind of influence do they exert on the result. Also, by adding new statistical data sets in the training database, the relationship between parameters changes in real time so the ANN adapts to the new paradigm to incorporate the many changes.

Doing this with the calculation method is almost impossible because it is a statical method that cannot be successfully applied in such a dynamical environment. The number of changes that have increased exponentially in the last two years make the previously predictions obsolete because they cannot adapt fast enough to the new statistical data. Changing the normative values for consumption behavior is such a slow process and requires stability in the statistical data sets which is incompatible with the current energetical situation. This makes us conclude that most countries make new energy policies based on inaccurate predictions and this comes with great problems of implementation. Most energy policies made a decade ago failed to be successfully applied due to this cause. They didn't take into consideration the dynamical aspect of the environment and the global changes due to black swan events.

2. 2021-2022 Energy crisis and the effects on energy consumption and energy policies regarding the residential sector

The year 2022 is marked by an energy crisis of an unprecedent effect due to it's particularities. The crisis was caused by a variety of economic factors. The post pandemic economic rebound generated a rapid growth in energy consumption as production almost doubled after the COVID restrictions were lifted. This situation outpaced the energy supply and escalated into a widespread global energy crisis following the Russian invasion of Ukraine.

Pressures in markets predated Russia's invasion of Ukraine, but Russia's actions have turned a rapid economic recovery from the pandemic – which strained all manner of global supply chains, including energy – into full-blown energy turmoil. Russia has been by far the world's largest exporter of fossil fuels, but its curtailments of natural gas supply to Europe and European sanctions on imports of oil and coal from Russia are severing one of the main arteries of global energy trade. All fuels are affected, but gas markets are the epicentre as Russia seeks leverage by exposing consumers to higher energy bills and supply shortages.

Prices for spot purchases of natural gas have reached levels never seen before, regularly exceeding the equivalent of USD 250 for a barrel of oil. Coal prices have also hit record levels, while oil rose well above USD 100 per barrel in mid-2022 before falling back. High gas and coal prices account for 90% of the upward pressure on electricity costs around the world.

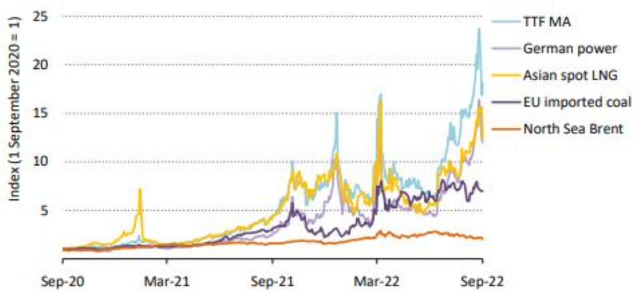

Figure 1: Evolution in selected energy price indicators since September 2020 [8]

To offset shortfalls in Russian gas supply, Europe is set to import an extra 50 billion cubic metres (bcm) of liquefied natural gas (LNG) in 2022 compared with the previous year. This has been eased by lower demand from China, where gas use was held back by lockdowns and subdued economic growth, but higher European LNG demand has diverted gas away from other importers in Asia.

The crisis has stoked inflationary pressures and created a looming risk of recession, as well as a huge USD 2 trillion windfall for fossil fuel producers above their 2021 net income.

Higher energy prices are also increasing food insecurity in many developing economies, with the heaviest burden falling on poorer households where a larger share of income is spent on energy and food. Some 75 million people who recently gained access to electricity are likely to lose the ability to pay for it, meaning that for the first time since we started tracking it, the total number of people worldwide without electricity access has started to rise. And almost 100 million people may be pushed back into reliance on firewood for cooking instead of cleaner, healthier solutions.

Faced with energy shortfalls and high prices, governments have so far committed well over USD 500 billion, mainly in advanced economies, to shield consumers from the immediate impacts. They have rushed to try and secure alternative fuel supplies and ensure adequate gas storage. Other short-term actions have included increasing oil- and coal-fired electricity generation, extending the lifetimes of some nuclear power plants, and accelerating the flow of new renewables projects. Demand-side measures have generally received less attention, but greater efficiency is an essential part of the short- and longer-term response.

New policies in major energy markets help propel annual clean energy investment to more than USD 2 trillion by 2030 in the STEPS, a rise of more than 50% from today. Clean energy becomes a huge opportunity for growth and jobs, and a major arena for international economic competition. By 2030, thanks in large part to the US Inflation Reduction Act, annual solar and wind capacity additions in the United States grow two-and-a-half-times over today's levels, while electric car sales are seven times larger. New targets continue to spur the massive build-out of clean energy in China, meaning that its coal and oil consumption both peak before the end of this decade. Faster deployment of renewables and efficiency improvements in the European Union bring down EU natural gas and oil demand by 20% this decade, and coal demand by 50%, a push given additional urgency by the need to find new sources of economic and industrial advantage beyond Russian gas. Japan's Green Transformation (GX) program provides a major funding boost for technologies including nuclear, low-emissions hydrogen and ammonia, while Korea is also looking to increase the share of nuclear and renewables in its energy mix. India makes further progress towards its domestic renewable capacity target of 500 gigawatts (GW) in 2030, and renewables meet nearly two-thirds of the country's rapidly rising demand for electricity.

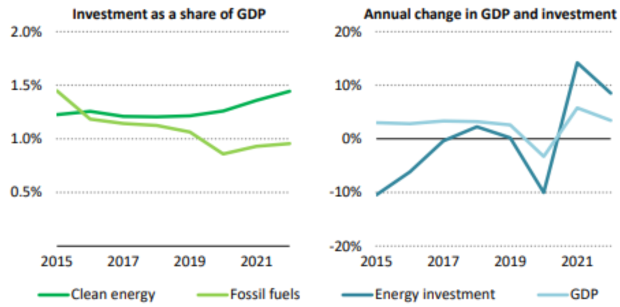

Figure 2: Historical energy investments and GDP trends [8]

As markets rebalance, renewables, supported by nuclear power, see sustained gains; the upside for coal from today's crisis is temporary. The increase in renewable electricity generation is sufficiently fast to outpace growth in total electricity generation, driving down the contribution of fossil fuels for power. The crisis briefly pushes up utilization rates for existing coal-fired assets but does not bring higher investment in new ones. Strengthened policies, a subdued economic outlook and high near-term prices combine to moderate overall energy demand growth. Increases come primarily from India, Southeast Asia, Africa and the Middle East. However, the rise in China's energy use, which has been such an important driver for global energy trends over the past two decades, slows and then halts altogether before 2030 as China shifts to a more services-orientated economy.

Today's high energy prices underscore the benefits of greater energy efficiency and are prompting behavioral and technology changes in some countries to reduce energy use.

Efficiency measures can have dramatic effects – today's light bulbs are at least four times more efficient than those on sale two decades ago – but much more remains to be done.

Demand for cooling needs to be a particularly focus for policy makers, as it makes the second-largest contribution to the overall rise in global electricity demand over the coming decades (after EVs). Many air conditioners used today are subject only to weak efficiency standards and one-fifth of electricity demand for cooling in emerging and developing economies is not covered by any standards at all. In the STEPS, cooling demand in emerging and developing economies rises by 2 800 terawatt-hours to 2050, which is the equivalent of adding another European Union to today's global electricity demand. This growth is reduced by half in the APS because of tighter efficiency standards and better building design and insulation – and by half again in the NZE Scenario.

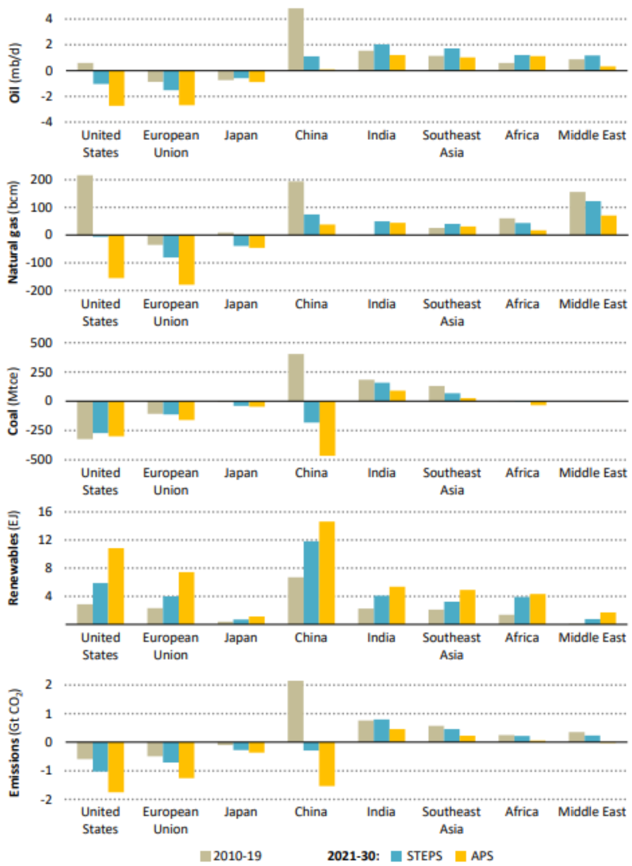

Figure 3: Energy demand growth by region and scenario 2021-2030 [8]

Concerns about fuel prices, energy security and emissions – bolstered by stronger policy support – are brightening the prospects for many low-emissions fuels. Investment in low-emissions gases is set to rise sharply in the coming years. In the APS, global low-emissions hydrogen production rises from very low levels today to reach over 30 million tonnes (Mt) IEA. CC BY 4.0. Executive Summary 23 per year in 2030, equivalent to over 100 bcm of natural gas (although not all low-emissions hydrogen would replace natural gas). Much of this is produced close to the point of use, but there is growing momentum behind international trade in hydrogen and hydrogen-based fuels. Projects representing a potential 12 Mt of export capacity are in various stages of planning, although these are more numerous and more advanced than corresponding projects to underpin import infrastructure and demand. Carbon capture, utilization and storage projects are also advancing more rapidly than before, spurred by greater policy support to aid industrial decarbonisation, to produce low- or lower-emissions fuels, and to allow for direct air capture projects that remove carbon from the atmosphere.

3. Theoretical considerations on Artificial Neural Networks (ANN)

An artificial neural network is defined as an evenly distributed information processor with the ability of experimental data storage and prediction on new input cases. The information processing module mimics the human brain activity forming patterns by studying the existing situations and applying the knowledge to generate predictions about new situations.

ANN's are used in the engineering field as an alternative method of analysis and prediction. Neural networks operate successfully in most cases where conventional methods fail, data analysis being applied at present to solve a variety of nonlinear problems such as pattern recognition. [3]

Instead of using complex rules and mathematical routines, ANN's are able to learn the key information patterns within a multidimensional information domain. In addition, neural networks successfully eliminate data entry errors and supplementary information irrelevant to the processes, becoming robust tools for data modeling and prediction [4].

4. The database construction for the ANN's training

The data for training the ANN was collected for a period of 12 months in different buildings from Romania, mainly in Cluj-Napoca city but also in other towns from the county. The data is spread out and evenly distributed over the length of the analyzed interval, so it covers a large area of values for accuracy in predicting future cases.

4.1 Selecting the input and output parameters

Given the available data, the following variables are chosen to represent the input parameters of neural network, being the input neurons of the network as well. We changed the input neurons from the lock-down period and replace them with the number of days people chose to work from home or were required to go to the company site.

- N representing the number of occupants;
- $D_{on\text{-}line}$ representing the number of days when people worked remote, from home;
- $D_{on\text{-}site}$ representing the number of days people were required to go to work on-site;
- S_h representing the total heated area [m^2];
- V representing the volume [m^3];
- $S_{anvelopă}$ representing the total outside surface [m^2];
- $S_{pereți}$ representing the outside wall surface [m^2];
- $S_{terasă}$ representing the terrase surface [m^2];
- $S_{fe.usi}$ representing the total outside windows and doors [m^2];
- $R_{pereți}$ being the thermal resistance of the walls [m²K/W];
- $R_{terasă}$ being the thermal resistance of the terrace [m²K/W];
- $R_{fe.uși}$ being the thermal resistance of the windows and doors, obtained as the ponderate mean regarding the surface [m²K/W]
- T being the average outside temperature mean of that specific month [°C]
- The variable chosen to represent the output parameter of the neural network and also the output neuron is:
- Q_h being the annual energy consumption for heating [kWh/year].

4.2 Construction of the ANN's training file

For constructing the database iterative calculations were made for 12 different input parameter measured monthly for a period of a year for 70 cases resulting in a number of 840 distinct sets of data.

The values were measured and recorded in Cluj-Napoca and nearby towns, Romania by using the gas and electric meters installed in these households and self-reported the values to the utility companies.

5. The construction and the training of the ANN

The program MathLAB, was used for the construction of the neural networks, for which an academic license was obtained.

In order to determine the right architecture of the network, a series of trials were made. The final architecture is composed of 14 neurons on the input layer (13 corresponding to the input parameters and one to the Bias), and one neuron on the output layer corresponding to the output parameter.

Regarding the neurons on the hidden layer a series of configurations were examined to reduce the errors, arriving at a number of 16 neurons.

The training process was conducted at a rate of 0.78 and the number of epochs was originally established at 5000. The last adjustment for the synaptic weights occurred after 4358 epochs.

The chart for the targeted values and the modeled values of the specific heat loss and the error between them for 70 cases on which the neural network gets validated are shown in Figure 4. It can be seen an almost perfect overlap between the two graphs, which demonstrates the networks capability to determine the required value with sufficient accuracy.

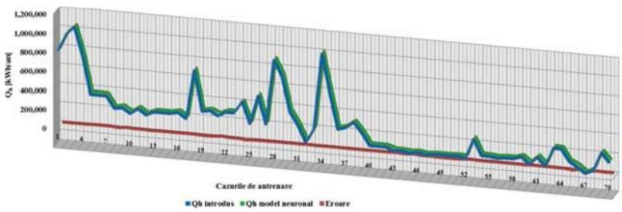

Figure 4: The chart for the targeted, the modeled values and the error for the ANN

The ANN was able to establish new vectors between the neurons according to the new set of data that differs from the one trained in previous versions.

By trying to make estimates and predictions we can conclude that the new neural network created and trained is able to respond to the requirements from this energetical situation.

6. Conclusions

The post-lockdown conditions and the invasion of Ukraine generated unprecedented changes in the energy policies across all countries and started an accelerated process of gaining energetical independency and stability, Structural changes in energy demand and consumption have been observed in the (a) short-term versus long-term expectations, (b) different sectors of the energy industry, (c) residential versus non-residential consumptions, (d) peak demand patterns, (e) consumption philosophy during and after lockdowns, (f) consumed products, and (g) energy intensities in different regions.

The application of the neural network in order to determine the energy consumption in residential buildings can be done successfully due to their ability to overcome the problems of non-linearity between the input parameters and the values to be calculated. This method can be used for all kind of predictions in energy consumption areas, thermal and electric energy being the first to be experimented in this case. ANN'S must be trained and updated to new sets of statistical data in order to overcome the dynamic evolution of energy consumption behavior affected by price surges and instability in production and energy sources. Once trained, the artificial neural networks can accurately make predictions better than any other method for as long as the situations remain stable. In order to make them work in a dynamic environment we have to include all the new sets of data in retraining them constantly.

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